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Left vertical segmentation of 2-D heart MRI images using U-net network

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ABSTRACT

Medical image processing has benefited greatly from advances in artificial intelligence, especially through the use of artificial neural networks. U-Net is an artificial neural network architecture that has proven successful in medical image segmentation tasks. Therefore, this study aims to combine the power of U-Net networks with 2-D cardiac MRI images to achieve accurate and automatic left vertical segmentation of the heart. By having a tool that can automatically segment the left vertical heart, doctors and researchers will be able to save valuable time in medical image analysis, while increasing accuracy and consistency in the assessment of heart structure. The results of this research will contribute to technological developments in the field of cardiovascular medicine and improve the care of patients with heart disease. Based on the work that was done and the results that were reported in Tabel I, the accuracy at the time of validation for full heart coroners, core heart coroners, and augmenting heart coroners was, respectively, 90.22%.

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1. INTRODUCTION

MRI (Magnetic Resonance Imaging) is an important medical imaging technique in the diagnosis and monitoring of heart diseas(Gomathi, 2022). 2-D cardiac MRI images are a valuable source of information for the evaluation of a patient's heart condition (*Menggunakan Metode Homotopy Tree Oleh : Kunti Eliyen*, 2013). However, in the context of cardiac MRI image analysis, one of the main challenges is the accurate segmentation of anatomical structures, such as the left vertical portion of the heart(Xu et al., 2022).

Left vertical segmentation of the heart in cardiac MRI images is a critical step in various medical applications, such as treatment planning and heart disease monitoring(Experts et al., n.d.). For example, in cardiac surgery planning, accurate information about the left vertical geometry of the heart is critical to determining the most appropriate procedure for the patient (Angga et al., n.d.; Valente et al., 2014). Additionally, in cardiac disease monitoring, precise segmentation of the left ventricle of the heart allows early detection of pathological changes and disease progression (Patterson et al., 2021; Seo et al., 2019; Yasmin et al., 2021).

Medical image processing has benefited greatly from advances in artificial intelligence, especially through the use of artificial neural networks (Anwar et al., 2018; Mehdy et al., 2017; Widyantara et al., 2015; Zhou et al., 2019). U-Net is an artificial neural network architecture that has proven successful in medical image segmentation tasks(Charmchi, 2018). Therefore, this study aims to combine the power of U-Net networks with 2-D cardiac MRI images to achieve accurate and automatic left vertical segmentation of the heart (Jolly, 2006; Tsadok et al., 2013; Widyantara et al., 2015).

By having a tool that can automatically segment the left vertical heart, doctors and researchers will be able to save valuable time in medical image analysis, while increasing accuracy and consistency in the assessment of heart structure(Wang et al., n.d.). The results of this research will contribute to technological developments in the field of cardiovascular medicine and improve the care of patients with heart disease(Bagus et al., 2020).

2. RESEARCH METHOD

2.1. Data Source

This study uses initial data from the Multi Brain heart Image Segmentation (BRATS) 2017 project (Narayanan et al., 2019; Slama et al., 2022). The MRI data from 210 patients with HGG-deficient heart coroner and 75 patients with LGG-deficient heart coroner will be used for 20% data validation and 80% data training in BRATS 2017. There are four types of MRI data available for each patient: T1-weighted (T1), image T1-weighted with gadolinium contrast (T1c), T2-weighted (T2), and Fluid Attenuated Inversion Recovery (FLAIR)(Jantung, 2013). In addition, manual segmentation using four intra-coroner class is available for each patient: (1) necrosis, (2) edema, (3) non-enhancing, and (4) enhancing coroner(Irshad et al., 2023). This manual segmentation is used as a baseline for ground truth in model segmentation during training and validation(Hariyadi, n.d.).

2.2. System Overview

The following block diagram shows the general flow of the coroner heart diagnosis system based on MRI scans, as shown in figure 1.

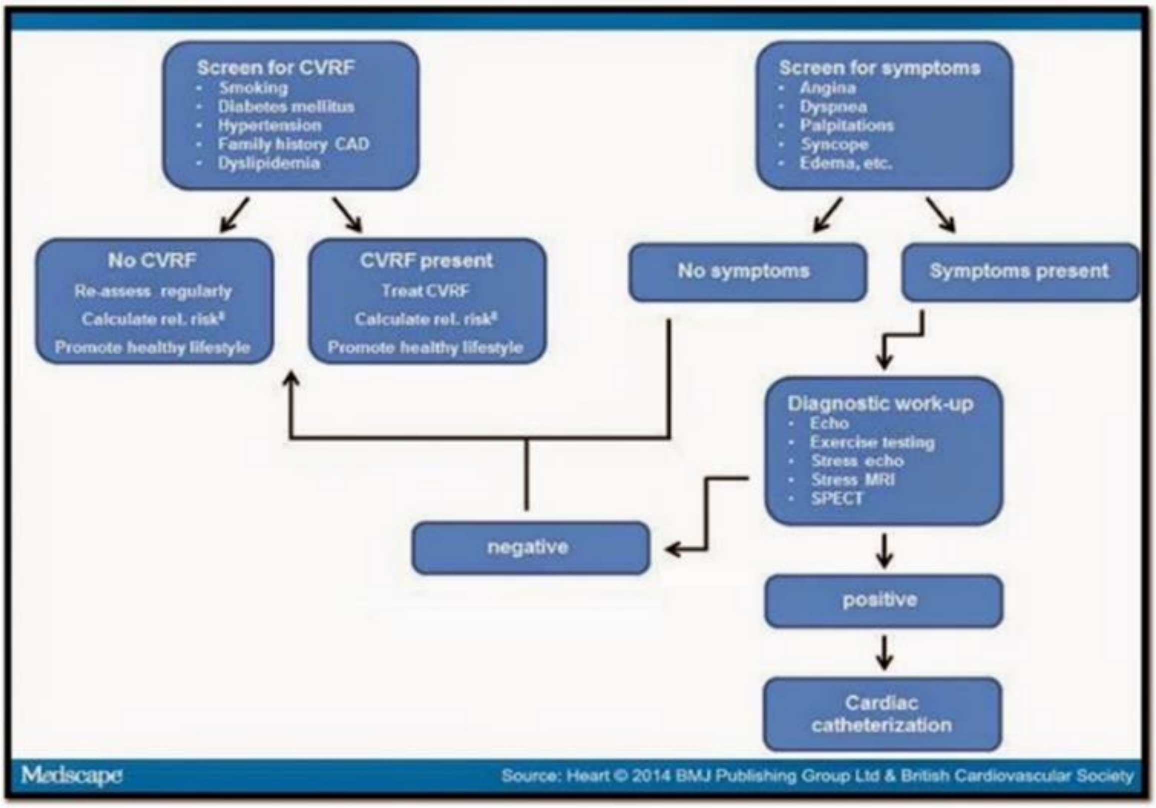

Figure1. Overview System

In the above diagram, an MRI scan may be shown before it is processed by the optimal U-NET algorithm through a few more steps. The N4ITK bias correction process is used to reduce noise present in MRI scan data; this technique is very useful for minimizing artifacts in the classification process (Yin & Wang, 2022). Then, in order to increase the number of datasets, the augmentation process is carried out using both vertical and horizontal flips in this particular study(Elektronika & Surabaya, 2020). Algorithm U-NET will carry out the learning process through the training and validation phases, resulting in the creation of a data model (Basyid et al., 2014; Ma et al., 2019). The data model is an array of MRI coroner heart samples that have previously been cleaned up by the U-NET algorithm in order to produce a data set (Ramadhan et al., 2010).

During a continuous experiment, accuracy and loss will be measured at each iteration (epoch) using the rumus Dice Coefficient. The Dice Coefficient represents the overlap area between two samples(Liao et al., 2015). This ranges from 0 to 1, where a Dice Coefficient of 1 indicates the best results. This function is initially designed for binary data and can be interpreted based on the following heart coroner:

$$Dice = \frac{2|A \cap B|}{|\bar{A}| + |B|} \quad (1)$$

In this case, $|A \cap B|$represents the number of elements in set A and |B| represents the number of elements in set B. In contrast, to calculate the loss or result of this model, we use the Soft Dice Coefficient function, which uses the 1-Dice

3. RESULTS AND DISCUSSION

The study is conducted using the BRATS 2017 dataset, which is divided into training and validation datasets with an 80:20 ratio. In the U-Net algorithm that will be evaluated, there are several hyperparameters and other parameters related to the Adam Optimizer's optimization function. The values for the hyperparameters are as follows: epoch = 80, beta ( ) = 0.9, batch size (bz) = 5, learning rate (lr) = 0.0001. The evaluation matrix is divided into three heart regions: a) Complete/Full heart (necrosis, edama, enhancing, and non-enhancing heart); b) Heart coroner region (Complete heart coroner); and c) Enhancing heart region.

Figure 2. Comparison of Loss Fase Training and Validation in the Full heart Segmentation Process

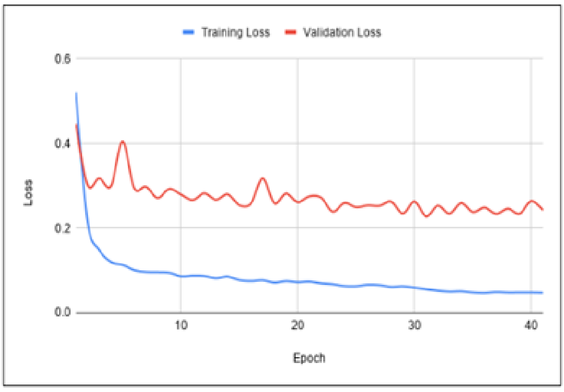

Figure 3. Comparison of Acceptance Phase Training and Validation in the ET heart Segmentation Process

Based on figure 2–3, it can be inferred that the U-Net model's graph does not indicate an overfitting or underfitting condition, but rather points to a graph that is approaching convergence. Underfitting is a phenomenon when a biased model is unable to accurately predict the data from different datasets, making it unable to produce reliable predictions from training or validation data. Conversely, overfitting occurs when a developed model places too much emphasis on the current training dataset, making it incapable of making accurate predictions when given other datasets. The number of epochs in this study is 80; however, due to perangkat keterbatasan, the researchers implemented an early stop monitor. The early stop monitor is a condition in which the training phase is completed before the end of the period. One condition that is applied is that if there is an increase in arousal per ten epochs, the training phase will be completed.

During the complete heart coroner segmentation learning process, U-NET method did not experience increasing accuracies during the 47 epoch, resulting in U-NET becoming inactive during that period. The same conditions were also observed when educational activities were conducted in the heart coroner core region, which did not experience an increase in arithmetic during the 47, resulting in a halt to the educational process during that period. promoting heart coroner during the -73. The next step is evaluating each model individually.

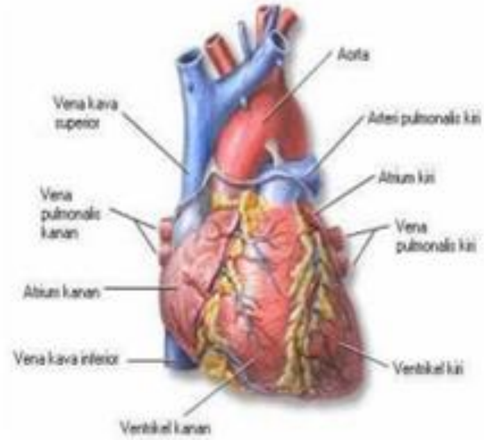

Figure 4. parts of the heart

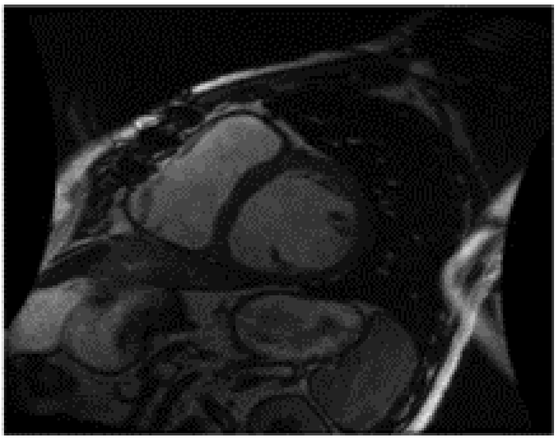

Figure 5. Result MRI

Table 1. Accuracy results

Segmentasi	Epoch	Accuracy	Loss
Full Heart Coroner	78	90,22%	0,2
Core Heart Coroner	45	78,09%	0,22
Enhancing Heart Coroner	72	80,20%	0,2

Based on Table I, the Full Heart coroner segmentation process yielded the highest accuracies when compared to other results, owing to the largest and clearest coroner area when compared to other coroner areas. Tables 4 and 5 present the results of the predicted jantung coroner segmentation compared to the manual segmentation performed by the doctor. It can be seen that the results of automatic segmentation yield lower margins than those of manual segmentation.

4. CONCLUSION

Based on the work that was done and the results that were reported in Tabel I, the accuracy at the time of validation for full heart coroners, core heart coroners, and augmenting heart coroners was, respectively, 90.22%, 78.09%, and 80.20%. For further analysis, it is recommended to apply optimization functions such as LReLU, PReLU, or ELU in addition to varying data augmentation (rotation, shift, blur, and so on) to improve dataset quality and achieve better results for coroner segmentation. For future development of this study, it is recommended to consider integration with other technologies such as more advanced machine learning and deep learning, as well as 3D image data for more detailed segmentation. In addition, collaboration with medical experts and cardiac specialists is an important step to ensure high medical relevance and more effective clinical application. In addition, exploring the use of a wider and more diverse range of patient data can help improve the generalizability of the model. Finally, a focus on data security and patient privacy remains a priority in the development of this study to ensure compliance with applicable ethical standards and medical data privacy regulations.

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